Predicted information gain and convolutional neural network for prediction of gait periods using a wearable sensors network

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Abstract— **This work presents a method for recognition of walking activities and prediction of gait periods using wearable sensors. First, a Convolutional Neural Network (CNN) is used to recognise the walking activity and gait period. Second, the output of the CNN is used by a Predicted Information Gain (PIG) method to predict the next most probable gait period while walking. The output of these two processes are combined to adapt the recognition accuracy of the system. This adaptive combination allows us to achieve an optimal recognition accuracy over time. The validation of this work is performed with an array of wearable sensors for the recognition of level-ground walking, ramp ascent and ramp descent, and prediction of gait periods. The results show that the proposed system can achieve accuracies of 100% and 99.9% for recognition of walking activity and gait period, respectively. These results show the benefit of having a system capable of predicting or anticipating the next information or event over time. Overall, this approach offers a method for accurate activity recognition, which is a key process for the development of wearable robots capable of safely assist humans in activities of daily living.**

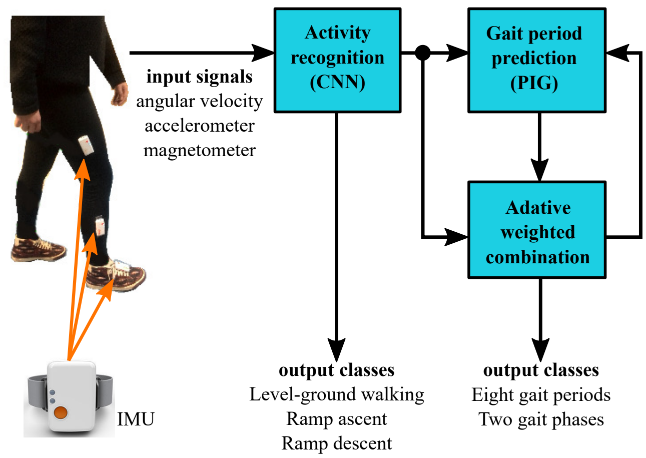

Fig. 1. Recognition of activities and prediction of gait periods using CNN and PIG models and an adaptive weighted combination approach.

I. Introduction

Walking is the capability that allows humas to translate from one place to another and undertake activities of daily living (ADLs) independently [1]. This capability can be affected by the old age reached by the person [2]. Wearable robots can assist humans with reduced mobility or mobility impairments in order to perform activities of daily living [3], [4], [5]. In recent years, wearable assistive robots have shown rapid improvements in the materials and sensors employed in their design and development [6], [7], [8], [9]. In contrast, computational methods for recognition and prediction of movement intention have not shown the same progress.

Machine learning (ML) offers robust computational methods for recognition and prediction tasks. Dynamic Bayesian Networks (DBN) have shown to be capable of identifying walking activities on different terrains, using inertial measurement units (IMU) and electromyography (EMG) sensors [10], [11], [12]. Deep Learning (DL) techniques, based on Convolution Neural Networks (CNN), have gained popularity for the identification and classification of human activities with vision and IMU sensors [13], [14], [15]. These works have shown good results, however, they do not use information about the next most probable activity over time, which is an aspect that can contribute to improve both speed and accuracy recognition of wearable assistive devices.

In this work, a Predicted Information Gain (PIG) and CNN are combined to recognise walking activities and predict gait periods. First, three locomotion activities (level-ground walking (LGW), ramp ascent (RA) and ramp descent (RD)) and eight gait periods (initial contact, loading response, mid stance, terminal stance, pre-swing, initial swing, mid swing and terminal swing) are recognised using a CNN and wearable sensors [16], [17]. Second, the output of the CNN is used by the PIG approach [18] to predict the next gait period while the person is walking. This prediction process is key to allow assistive robots to respond fast and accurately. Then the output from the CNN and PIG modules are combined to adapt the accuracy of the recognition process (Figure 1). This approach ensures that the system will rely more on information from the source (CNN or PIG) that is more reliable to make accurate decisions about the gait period performed by the subject along the gait cycle [19], [20].

The recognition and prediction of walking activities and gait periods is evaluated with participants performing multiple walking activities (LGW, RA and RD) and wearing three inertial measurement units (IMU) on the lower limbs. First, the accuracy for recognition of the walking activity and current gait period, being performed by the subject, is evaluated. Second, the prediction method is employed to observe the effects on the accuracy for the identification of gait periods. The experiments show that the recognition process improves by adaptively combining information from

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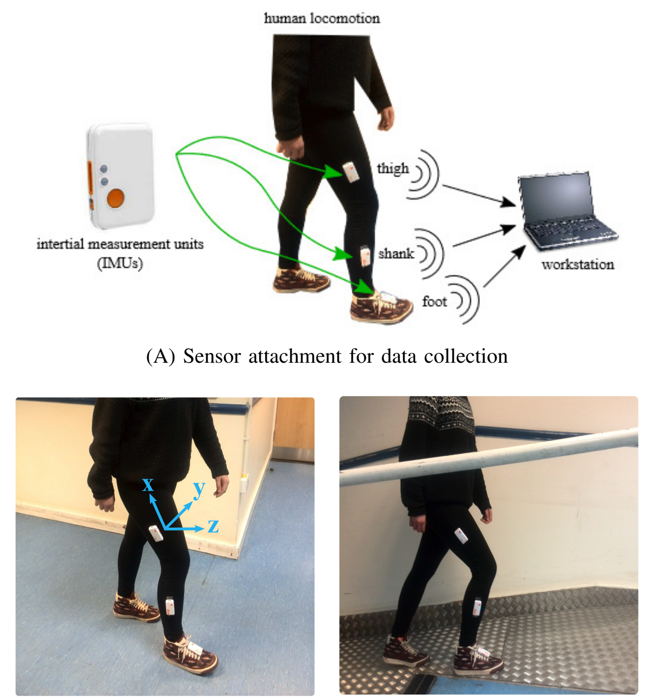


(A) Sensor attachment for data collection

(B) Level-ground walking

(C) Ramp ascent/descent

Fig. 2. Walking activities performed for data collection. (A) IMUs attached to the legs of subjects. (B) Level-ground walking activity (LGW) on a flat surface. (C) Ramp ascent (RA) and ramp descent (RD) activities. Participants repeated ten times each walking activity.

current observations and prediction process. Overall, this work shows the benefits in accuracy using systems capable of adapting based on observed and predicted sensory data.

II. Methods

A. Experimental protocol and data preparation

Twelve male subjects, without gait abnormalities, were recruited for data collection. The subjects' ages, heights and weights were from 24 to 34 years old, 1.74 m to 1.79 m, and 77.6 kg to 85 kg, respectively.

Data from three IMU sensors, attached to the thigh, shank and foot of participants, were collected for this research. These IMU sensors, from Shimmer Inc., have 9 DoF each and provide data from accelerometer, gyroscope and magnetometer. Data from all sensors were systematically collected and sent to a computer for their posterior processing and analysis by the proposed method. The detection of the start of the gait cycle, during the data collection process, was performed using a foot pressure insole. The attachment of sensors and data collection process are depicted in Figure 2A.

All subjects were asked to perform ten repetitions of LGW, RA and RD activities. A flat surface was used for LGW, and a ramp with an inclination of 8.5 deg was used for RA and RD, as shown in Figures 2B,C. Angular velocity, accelerometer and magnetometer signals, in x- y- and -z axes, were collected from each sensor at a sampling rate of 100 Hz. The signals collected were grouped into 12 datasets, where each dataset was composed of 27 sensor signals (3 signals $\times$ 3 axes $\times$ 3 sensors) and 200 sensor samples, from each gait cycle and walking activity. The datasets were divided into training (8 datasets) and testing (4 datasets) for validation of the proposed recognition and prediction methods. Figure 3A shows an example of these signals from a walking activity. For recognition and prediction of gait periods and gait phases, each gait cycle was divided into 1) initial contact, 2) loading response, 3) mid stance, 4) terminal stance, 5) pre-swing, 6) initial swing, 7) mid swing and 8) terminal swing periods, as shown in Figure 3B. Gait periods 1 to 5 belong to the stance phase, while the swing phase includes periods 6 to 8.

1) Recognition of activity and gait period: A CNN is employed for recognition of walking and gait periods. The CNN uses data from wearable sensors to recognise whether the human is performing LGW, RA or RD activity. The CNN is composed of two feature learning layers and one classification layer as shown in Figure 4. The first feature learning layer uses 32 5$\times$5 kernels for convolution and 32 2$\times$2 kernels for max-pooling. The second feature learning layer employs 16 3$\times$3 kernels for convolution and 16 2$\times$2 kernels for max-pooling. The classification uses a fully connected layer and softmax layer, which estimates the probability of the current walking activity. The CNN uses input data in a matrix of 27 signals $\times$ 25 data points from the segmentation of eight gait periods of the complete activity matrix (27 $\times$ 200). This format allows the CNN to estimate the gait period during the walking activity.

The CNN identifies the current walking activity and gait period, e.g., LGW and pre-swing (gait period 5). This approach can also determine whether the human is on the stance (gait period 1 to 5) or swing phase (gait period 6 to 8). The convolution and max-pooling layers of the CNN are implemented as follows:

$$x_{ij}^{l} = b_j + \sum_{a=0}^{m-1} \sum_{b=0}^{m-1} k_{ab} * y_{(i+a)(j+b)}^{l-1} \tag{1}$$

where x_{ij}^{l} is the output from the l-th layer of the j-th feature map on the i-th unit, b_j is the bias, and the convolution process is denoted by the operator $*$. The convolution is performed between the $m \times m$ k_{ab} kernel and the nonlinear output $y_{(i+a)(j+b)}^{l-1}$ from layer $l-1$. Equation (1) is used as input for the nonlinear function σ as follows:

$$y_{ij}^{l} = \sigma(x_{ij}^{l}) \tag{2}$$

where the nonlinear output from the l convolutional layer is y_{ij}^{l}. The nonlinear function σ defines the hyperbolic tangent function $\tanh$. Each convolution is followed by a max-pooling layer, which downsamples the input $u \times u$ region and returns its maximum value. The CNN uses 2 $\times$ 2 input region. This process is performed as follows:

$$y_{ij}^{l} = \max_{u \times u}(y_{ij}^{l-1}) \tag{3}$$

where maximum values from y_{ij}^{l-1} are assigned to y_{ij}^{l}. The output from the feature learning layer is fully connected to a

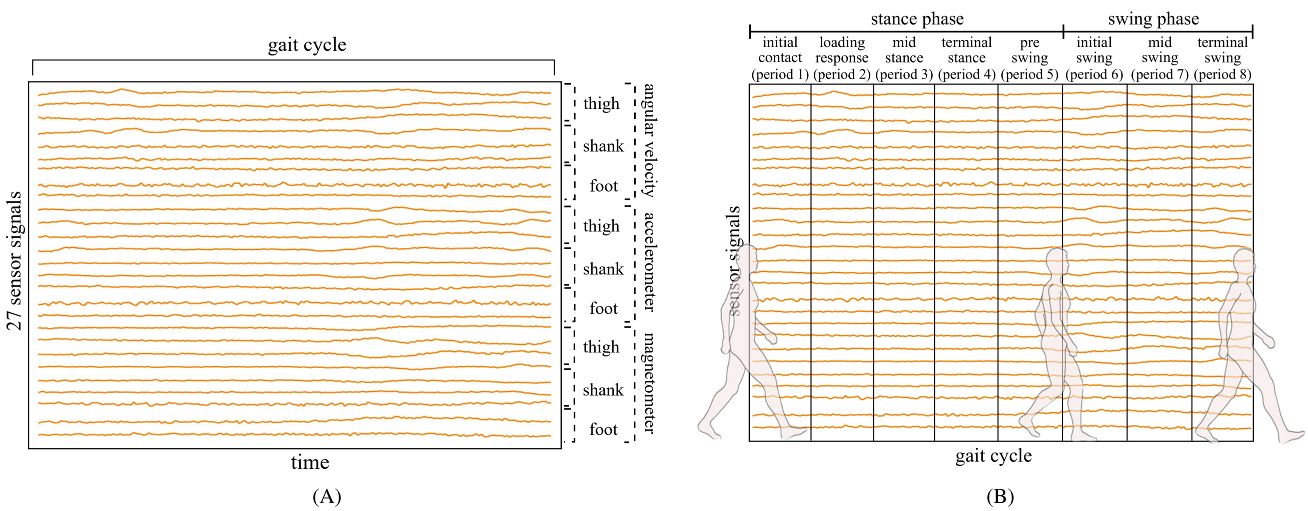


Fig. 3. Data used for the recognition and prediction processes with the proposed method. (A) Example data from gyroscope (x,y,z), accelerometer (x,y,z) and magnetometer (x,y,z) while walking. These signals are from the IMUs on the thigh, shank and foot of participants. (B) Example dataset segmented into two gait phases and eight gait periods for the recognition and prediction processes.

softmax layer, which estimates the probability for recognition of walking and gait periods, as follows:

$$P(c|y) = \frac{e^{y^T w_c}}{\sum_{n=1}^{N} e^{y^T w_n}} \tag{4}$$

$$\hat{c} = \arg\max_{c} P(c|y) \tag{5}$$

where c defines the (c_{activity}, c_{period}) pair, and $P(c|y)$ is the recognition probability given the current sensor data y. The weight vector and total number of classes are w and N, with $N = 24$ (3 walking activities $\times$ 8 gait periods). The most probable walking activity ($\hat{c}_{\text{activity}}$) and gait period ($\hat{c}_{\text{period}}$), defined by $\hat{c}$, are obtained with the *maximum a posteriori* (MAP) estimate as shown in Equation (5). The estimated walking activities and gait periods from the CNN are depicted in Figure 4. The development of assistive robots not only need to recognise the human activity but also to predict it. Next section presents a method based on adaptive combination of information for prediction of gait periods.

2) Prediction of gait periods: A Predicted Information Gain (PIG) method is used for the prediction of gait periods during walking. The PIG approach observes the information gained from transitions between gait periods performed at previous times $t-1$ during the walking activity. This process outputs the parameter Δ, which is used to estimate the next probable gait period. The predicted information gain approach is defined as follows:

$$\text{PIG} = \gamma \sum_{\text{s}^*} \hat{\Theta}_{\text{a,s,s}^*} \text{D}_{\text{KL}}\left(\hat{\Theta}_{\text{a,s}}^{\text{a,s,s}^*} || \hat{\Theta}_{\text{a,s}}\right) \tag{6}$$

$$\text{D}_{\text{KL}}\left(\hat{\Theta}_{\text{a,s}}^{\text{a,s,s}^*} || \hat{\Theta}_{\text{a,s}}\right) = \sum_{\text{s}^*}^{\text{N}} \hat{\Theta}_{\text{a,s}}^{\text{a,s,s}^*} \log\left(\frac{\hat{\Theta}_{\text{a,s}}^{\text{a,s,s}^*}}{\hat{\Theta}_{\text{a,s}}}\right) \tag{7}$$

The parameter $\hat{\Theta}$ denotes the estimated observations made by the CNN. The gait periods are $s = \{s_1, s_2, \ldots, s_N\}$ with

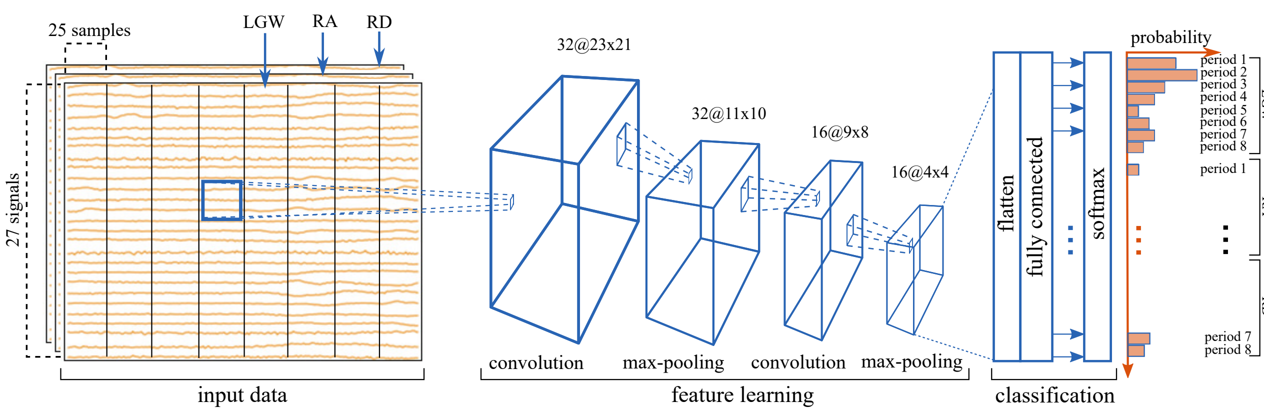


Fig. 4. CNN used for recognition of walking activities and gait periods. The CNN input data from the wearable sensors are grouped into matrices of 27 signals $\times$ 25 samples. The first feature layer uses 32 5$\times$5 kernels for convolution and 32 2$\times$2 kernels for max-pooling. The second layer uses 16 3$\times$3 kernels for convolution and 16 2$\times$2 kernels for max-pooling. The features extracted are used by a fully connected layer and softmax function for classification. The output layer shows the probability for recognition, at current time t, of each gait period for each walking activity.

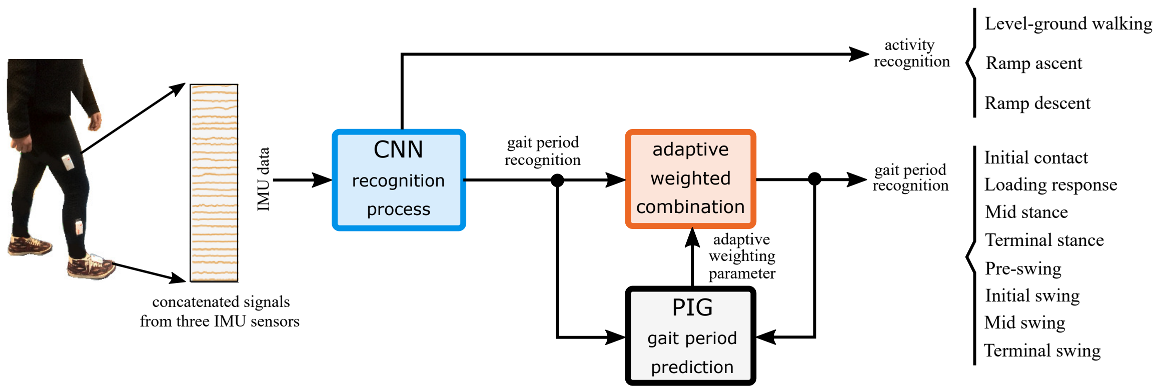


Fig. 5. Modules of the proposed method composed of a CNN module for recognition, a PIG module for prediction and a module for adaptive weighted combination of information sources. The CNN performs the recognition of walking activity and gait periods. The PIG method predicts the current gait period based on the observation of events over time. The recognition of gait periods from the CNN and the prediction performed by the PIG method are combined using a weighting parameter, which adapts its value based on the accuracy of predictions made by the PIG method. The adaptive weighted combination method will rely or assign more weight to the information source, CNN module or PIG method, that shows to be more accurate over time.

$N=8$, and transitions between these gait periods are $a = \{a_1, a_2, \ldots, a_N\}$ with $N=8$. The estimated observations for the current gait period s given a transition a are $\hat{\Theta}_{a,s}$. The hypothetical observations s^* for each transition a at previous gait period s are $\hat{\Theta}^{a,s,s^*}_{a,s}$. The hypothetical outputs s^* by a transition a in the current gait period s are $\hat{\Theta}_{a,s,s^*}$. Equation (6) is normalised by the parameter γ. The Kullback-Leibler Divergence ($\mathrm{D_{KL}}$) in Equation (7) provides the information that would have been lost for each transition observed at the previous decision times. The PIG value from Equation (6) is employed to update the transition matrix Γ_t to obtain the parameter Δ. This parameter shifts the probability of current gait periods, $P(c_{\text{period}}|y)$ for prediction of the next most probable gait periods, as follows:

$$\Gamma_t = \left(\frac{t-1}{t}\right)\Gamma_{t-1} + \left(\frac{1}{t}\right)\mathrm{PIG} \tag{8}$$

$$\Delta = \arg\max(\Gamma_t) \tag{9}$$

The position of the largest probability in Equation (9) is assigned to Δ to shift $P(c_{\text{period}}|y)$ for prediction of the gait periods for next time $t+1$, as follows:

$$P_{\text{period}_{t+1}} = P(c_{\text{period}} + \Delta|y) \tag{10}$$

where $P_{\text{period}_{t+1}}$ are the predicted gait periods. This prediction output is combined with the estimation of current gait periods using the adaptive weighting parameter described in the following section.

3) Adaptive combination of information sources: Humans combine multiple sources of information to improve the accuracy of their decisions. Here, a strategy based on the weighted combination of current and predicted information is presented to improve the accuracy of the recognition process. This weighted combination strategy is as follows:

$$\hat{P}_{\text{period}_t} = \alpha_t P_{\text{period}_t} + (1-\alpha_t)P_{\text{period}_{t+1}} \tag{11}$$

where $\hat{P}_{\text{period}_t}$ is the updated gait period probability from the adaptive combination of current and predicted gait periods. The weighting parameter, α, adapts over time based on the reliability of each information source. This adaptive process evaluates the error between the prediction of $P_{\text{period}_{t+1}}$, and the actual gait period $P_{\text{period}_t} = P(c_{\text{period}})$, as follows:

$$\xi_t = |P_{\text{period}_t} - P_{\text{period}_{t+1}}| \tag{12}$$

$$\alpha_t = \left(\frac{t-1}{t}\right)\alpha_{t-1} + \left(\frac{1}{t}\right)\xi_t \tag{13}$$

where ξ_t is the error of the predicted gait period and the actual recognised gait period. This value is used to update the parameter α. Equation (12) indicates that if the distance between the prediction and actual recognition is small, then the error ξ and weighted parameter α will be small, relying more on the predictions from the PIG method. In contrasts, if the distance is large, then ξ and α will be large, making the recognition system to rely more on the current recognised gait periods. The recognition, prediction and weighted combination processes are presented in Figure 5.

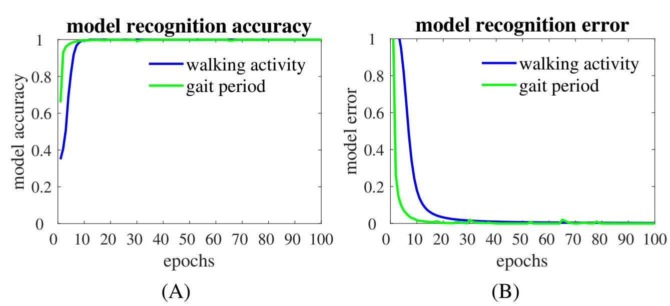
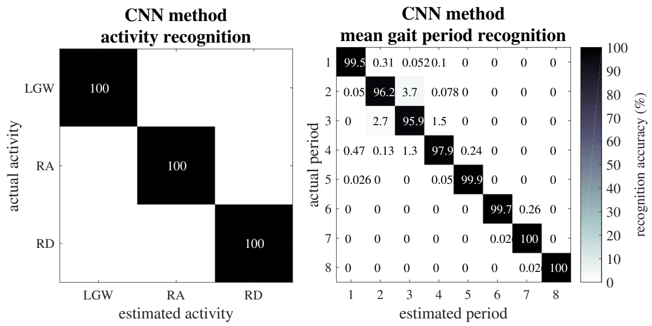


Fig. 6. CNN model training for the recognition of the walking activity (blue curve) and gait period (green curve). (A) Accuracy and (B) error against the number of epochs for recognition processes with the CNN model.



(A) (B)

Fig. 7. CNN model accuracy for recognition of walking activity and gait periods using new data. (A) Mean recognition of LGW, RA and RD activities. (B) Mean recognition accuracy of gait periods; 1) initial contact, 2) loading response, 3) mid stance, 4) terminal stance, 5) pre-swing, 6) initial swing, 7) mid swing and 8) terminal swing, over all walking activities.

III. Experiments and Results

A. Recognition of walking activity and gait period

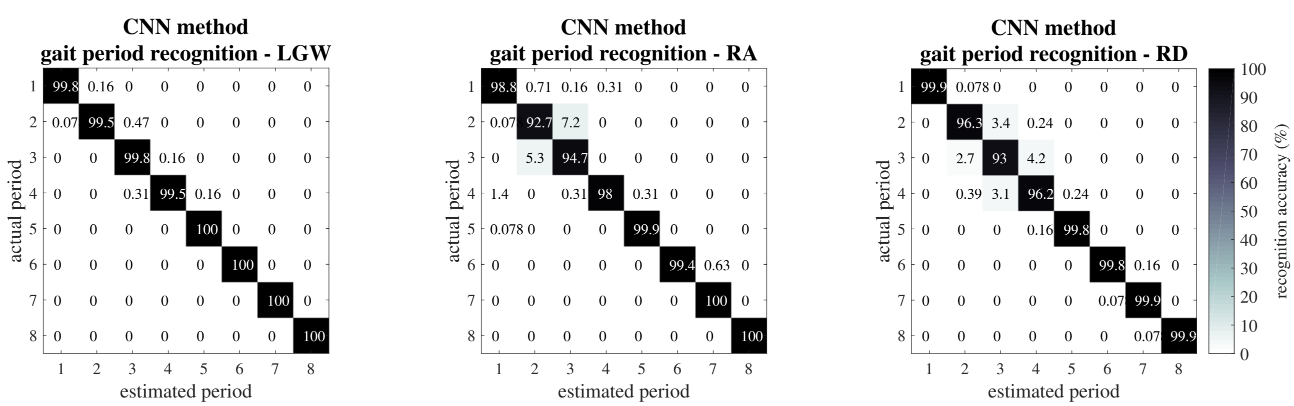
In this experiment, LGW, RA and RD activites were used to validate the recognition method. Three IMUs on the legs of participants were used to collect angular velocity, accelerometer and magnetometer signals. Figure 3A shows an example of these signals from the walking cycle, which is segmented into eight gait periods (Figure 3B) for recognition of initial contact, loading response, mid-stance, terminal stance, pre-swing, initial swing, mid-swing and terminal swing. Data from 12 participants was grouped into eight and four datasets to train and test the proposed method.

The CNN accuracy and error of the training process was evaluated with random samples from the training datasets (Figures 6A,B). This result shows that walking (blue curve) and gait period (green curve) are recognised with mean accuracy of 100% (error of 0%) within 100 epochs. The CNN was also evaluated using samples from the test datasets and Figure 7A shows that each walking activity was recognised with mean accuracy of 100%, while gait periods were recognised with mean accuracy of 98.63% (Figure 7B). The accuracies of 97.88% and 99.90%, for recognition of stance and swing phases were obtained by averaging the accuracies from gait periods 1 to 5, and gait periods 6 to 8, respectively. The recognition of walking and gait periods allow us to know the state of the human body while walking. The recognition accuracy of gait periods for each walking activity is shown in Figure 8, with mean accuracies of 99.82%, 97.93% and 98.10% for LGW, RA and RD, respectively.

B. Prediction of gait periods

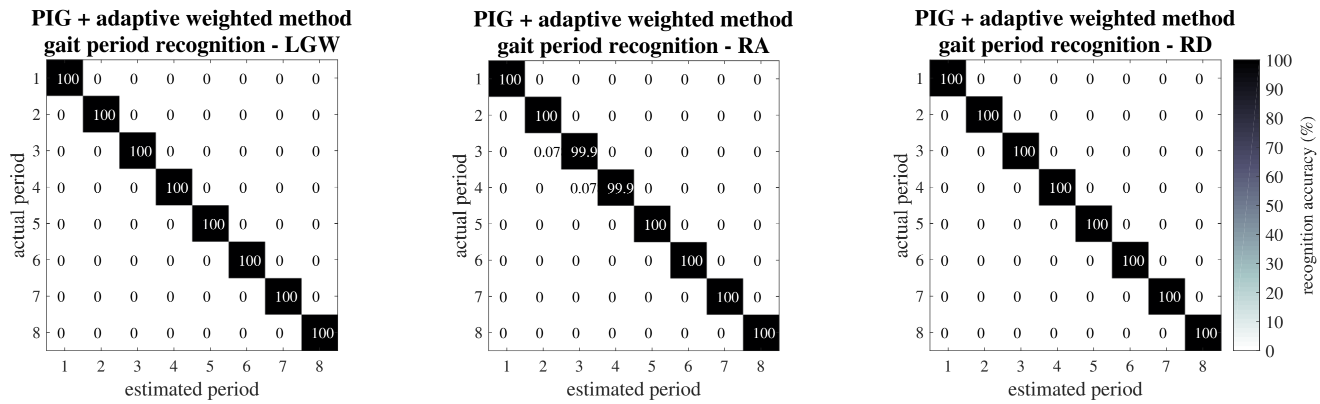
Prediction of gait periods is important in order to achieve better control of assistive robots, given that they can anticipate and adapt their actions to expected events. The results for gait period recognition for each walking activity using the prediction approach are shown in Figure 9. The recognition accuracy was improved for all walking activities, where level-ground walking, ramp ascent and descent, achieved mean recognition accuracies of 100%, 99.97% and 100%, respectively. These results show an improvement over the recognition process without the predictive approach.

This experiment used the prediction output from the PIG model and the adaptive weighted combination approach. The combination of current and predicted gait periods is adaptively weighted, relying more on the information source that shows to be more accurate. For example, at the beginning of the walking activity the parameter $\alpha = 0$, and then the recognition process relies on the CNN model only and does not use information from the PIG model. Then, the adaptive parameter modifies its value, gradually increasing and decreasing between $\alpha = 0$ and $\alpha = 1$, according to the predictions made by the PIG model and the accuracy of the recognition output from the CNN model. For instance, the weighting parameter keep as small value when the recognition from the CNN only is accurate, which makes the process to rely only on the current observations from sensors. However, when the CNN does not achieve accurate, the weighting parameter increases its value to use more information from the prediction process, and thus improve the recognition process.



(A) (B) (C)

Fig. 8. Recognition of gait periods for each walking activity using the CNN model and wearable sensor data. (A) Gait period recognition for (A) level-ground walking (LGW), (B) ramp ascent (RA) and (C) ramp descent (RD) with mean accuracy of 99.82%, 97.93% and 98.10%, respectively. LGW provides the highest accuracy while ramp ascent shows the lowest accuracy.



(A) (B) (C)

Fig. 9. Recognition of gait periods using the PIG method and the adaptive weighted combination approach. (A) Gait period recognition for (A) level-ground walking (LGW), (B) ramp ascent (RA) and (C) ramp descent (RD) with mean accuracy of 100%, 99.97% and 100%, respectively. The recognition accuracy of gait periods for all walking activities is improved by the use of the weighted information obtained from the predictive approach.

Overall, the results show that the method composed of the CNN and PIG models and the adaptive weighting approach can be used to make assistive robots capable of adapting the combination of sensor data to improve the accuracy of recognition processes such as in walking and gait periods.

IV. Conclusion

This work presented a method for recognition of walking activity and prediction of gait periods composed of CNN and PIG models for recognition and prediction processes and an adaptive weighted combination approach. Three wearable sensors attached to the legs of participants were used for data collection. Experiments based on the recognition of three walking activities and prediction of eight gait periods were undertaken to validate the proposed method. First, the CNN showed to be able to recognise accurately the walking activities performed by participants. Second, the predicted process was able to estimate the most probable gait period for the next time step during walking. Third, the output from the CNN and PIG models were combined using an adaptive weighting parameter to optimise the performance in accuracy of the recognition and prediction processes. The results showed that adaptively combining current and predicted output can improve the recognition accuracy and potentially the speed as well, which are key aspects to develop wearable robots capable of recognising human movements to assist them in activities of daily living.

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